Available online at www.sciencedirect.com
ScienceDirect
Renewable and Sustainable Energy Reviews 13 (2009) 721–735
RENEWABLE & SUSTAINABLE ENERGY REVIEWS
www.elsevier.com/locate/rser

Community-scale renewable energy systems planning under uncertainty—An interval chance-constrained programming approach

Y.P. Cai [a], G.H. Huang [b,*], Z.F. Yang [c], Q.G. Lin [a], Q. Tan [a]

[a] *Environmental Systems Engineering Program, Faculty of Engineering, University of Regina, Regina, Saskatchewan, Canada S4S 0A2*
[b] *Department of Civil and Environmental Engineering, University of Waterloo, Waterloo, Ontario, Canada N2L 3G1*
[c] *State Key Laboratory of Water Environment Simulation, School of Environment, Beijing Normal University, Beijing 100875, China*

Received 7 November 2007; accepted 7 January 2008

Abstract

In this study, an inexact community-scale energy model (ICS-EM) has been developed for planning renewable energy management (REM) systems under uncertainty. This method is based on an integration of the existing interval linear programming (ILP), chance-constrained programming (CCP) and mixed integer linear programming (MILP) techniques. ICS-EM allows uncertainties presented as both probability distributions and interval values to be incorporated within a general optimization framework. It can also facilitate capacity-expansion planning for energy-production facilities within a multi-period and multi-option context. Complexities in energy management systems can be systematically reflected, thus applicability of the modeling process can be highly enhanced. The developed method has then been applied to a case of long-term renewable energy management planning for three communities. Useful solutions for the planning of energy management systems have been generated. Interval solutions associated with different risk levels of constraint violation have been obtained. They can be used for generating decision alternatives and thus help decision makers identify desired policies under various economic and system-reliability constraints. The generated solutions can also provide desired energy resource/service allocation and capacity-expansion plans with a minimized system cost, a maximized system reliability and a maximized energy security. Tradeoffs between system costs and constraint-violation risks can also be tackled. Higher costs will increase system stability, while a desire for lower system costs will run into a risk of potential instability of the management system. They are helpful for supporting (a) adjustment or justification of allocation patterns of energy resources and services, (b) formulation of local policies regarding energy consumption, economic development and energy structure, and (c) analysis of interactions among economic cost, system reliability and energy-supply security.

Keywords: Community; Decision making; Energy systems; Environment; Greenhouse gas; Management; Renewable energy; Uncertainty

Contents

1. Introduction

Management of renewable energy resources is crucial for many urban communities throughout the world. The rising fossil fuel prices, increasing environmental- and health-impact concerns, shrinking energy reserves, and varying legislational,

* Corresponding author. Tel.: +1 306 585 4095; fax: +1 306 585 4855.
E-mail address: huang@iseis.org (G.H. Huang).

1364-0321/$ – see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.rser.2008.01.008

geographic, economic and political conditions are having significant effects on renewable energy management practices [1–7]. Also, energy-supply security, environmental protection and resources conservation are continuing to be challenges faced by decision makers in many communities [6,8]. However, in renewable energy management (REM) systems, there are many complex processes that should be considered by decision-makers, such as energy production, conversion, transmission and utilization as well as the resulting greenhouse gas (GHG)/pollutant emissions. Moreover, many system parameters (such as resource availability, facility capacity, production efficiency and allocation target, as well as their interrelationships) may appear uncertain and may be presented in fuzzy, probabilistic and/or interval formats. Such uncertainties might be further complicated by not only the natural variations of renewable energy resources, but also the associated economic and environmental implications for their utilization. These uncertainties would affect the related optimization processes and the generated decision schemes [5,9,10]. Therefore, effective planning for REM systems under various uncertainties is desired.

Previously, a number of systems analysis techniques were employed for assisting in the formulation of long-term energy management plans, which were helpful for analyzing relationships among various socio-economic and environmental subsystems [11–22]. Among them, optimization methods were effective in providing desired decision alternatives under varying system conditions [23–25]. Over the past decades, numerous models were developed in dealing with planning issues for energy management systems [18–20,26–31]. For example, Brookhaven Energy System Optimization Model (BESOM) was used to identify optimal mixing patterns of energy resources, technologies and investments under the minimum economic cost at multiple scales [15,24,32]. Time-stepped energy system optimization model (TESOM) was proposed as a consecutive BESOM-type optimization modeling system for supporting energy management over a short term [33]. Market allocation model (MARKAL) was developed as a large-scale, technology-oriented energy-activity analysis model. Based on MARKAL, sectors of energy production, conversion, processing, transmission and utilization were incorporated within a general framework to help formulate cost-effective energy management plans [17,20,25,34–36]. Multiple Energy System of Australia (MENSA) was developed to identify optimal combinations of demand- and supply-side technologies under an objective of the least economic cost [37]. Energy flow optimization model (EFOM) was established as an engineering-oriented bottom-up model for national energy management systems planning and was widely used in many European countries [24,38–41]. Chinese et al. developed a linear programming model to assess technical and economic feasibilities of renewable energy utilizations to minimize GHG emissions [42]. There were also a number of software packages, such as Long-range Energy Alternatives Planning System (LEAP), New Earth 21 Model (NE21), National Energy Modeling System (NEMS) and Energy 2020, which were developed to evaluate environmental and economic effects of energy activities [16,43–47]. Recently, a few researchers also tackled REM systems planning through the systems analysis techniques. For instance, Khan et al. used a life-cycle-assessment method to examine effects of policies and regulations on the REM system in St John's, Canada [48]. Ashok developed a linear programming model for the planning of REM systems in India [49]. Rehman et al. presented a mixed-integer linear programming model for evaluating renewable energy utilization technologies in a REM system [31]. El-Shatter et al. proposed an integrated wind/PV/fuel-cell power-generation system for the management of renewable energy resources; in their study, power generation from renewable energy sources could be maximized under minimized economic costs over a long-term planning period [50]. Kazmerski made a comprehensive investigation of technologies and research works related to Photovoltaics [2]. Polatidis and Haralambopoulos examined the existing REM systems that were practically used throughout the world [51]. They also proposed a method to decompose complex energy activities for REM systems planning. Iniyan and Sumathy used a modified linear programming model for supporting energy systems planning in Hong Kong, trying to promote the utilization of renewable energies in this city [52].

However, most of the previous studies could hardly reflect complex linkages that exist among different energy activities and their socio-economic and environmental implications in a multi-sector, multi-period, and multi-objective context. Also, these studies could not effectively handle uncertainties associated with dynamic changes of system conditions, especially for temporal and/or spatial variations of renewable energy resources. On the other hand, a number of inexact programming methods were developed for dealing with various uncertainties in planning problems, which were generally based on interval linear programming (ILP), fuzzy linear programming (FLP) and stochastic mathematical programming (SMP) [5,53–57]. These methods improved upon the conventional approaches through direct integration of uncertain information (expressed as interval values and/or possibilistic/probabilistic distributions) into the modeling formulations [9,53]. Their primary advantage was the flexibility in modeling the decision process and generating desired decision alternatives. In the past decades, inexact optimization methods were successfully applied to the management of municipal solid waste, water resources and air quality [5,9,53–61]; however, few applications to energy systems planning were reported.

Therefore, it is desired that an integrated optimization method be provided for handling the uncertainties and complexities in REM systems planning. The objective of this study is thus to develop an inexact community-scale energy model (ICS-EM) for supporting REM systems planning under uncertainty. Both CCP and ILP will be incorporated within a MILP context. Uncertainties expressed as not only probability density functions (PDFs) but also interval values will be effectively handled. More importantly, it will be used for quantitatively analyzing various policies related to renewable energy adoption, helping formulate efficient REM systems and identifying optimal patterns for energy utilization at a

community scale. A hypothetical case study will then be provided for demonstrating applicability of the developed model. In detail, this study would (a) tackle competitive and interactive relationships among various sectors and processes in a REM system, (b) search for optimal patterns of energy generation, conversion and consumption with minimized economic costs, (c) generate a number of decision alternatives under various system conditions, allowing comprehensive analysis of tradeoffs between social and economic objectives, (d) facilitate the reflection of multiple forms of uncertainties in the REM system, and (e) apply the proposed ICS-EM to long-term REM systems planning, such that plans for cost-effective allocation of energy resources and services will be generated.

2. Renewable energy management systems at a community level

Energy is critical in supporting people's daily life and continued human development [4]. Although great successes have been achieved, more than 2 billion people are still lacking of sufficient energy supply throughout the world [3,4,6,7,62]. Particularly, for communities in developing countries or remote areas in developed countries, large-scale fossil fuel supply and grid extension might be impractical due to economic and environmental concerns. Locally available renewable energy sources might thus be the primary option for energy supply [6,8]. Moreover, REM systems at these communities have complex interactions with a number of subsystems (Fig. 1). Generally, energy activities/services are responsible for relevant infrastructural investments and pollutant/GHG emissions, and have impacts on local ecosystems. However, institutional measures and socio-economic activities would also have effects on the REM systems through various policies, actions and strategies, which would then have indirect impacts on the other components within the community. On the other hand, there are limited energy resources and economic investments (particularly for locally available renewable energy resources), which implies necessity for effective use of them. Therefore, energy systems planning will help to design a variety of system activities under these limited "allowances" for energy allocation and resource consumption, in order to realize desired socio-economic and environmental objectives.

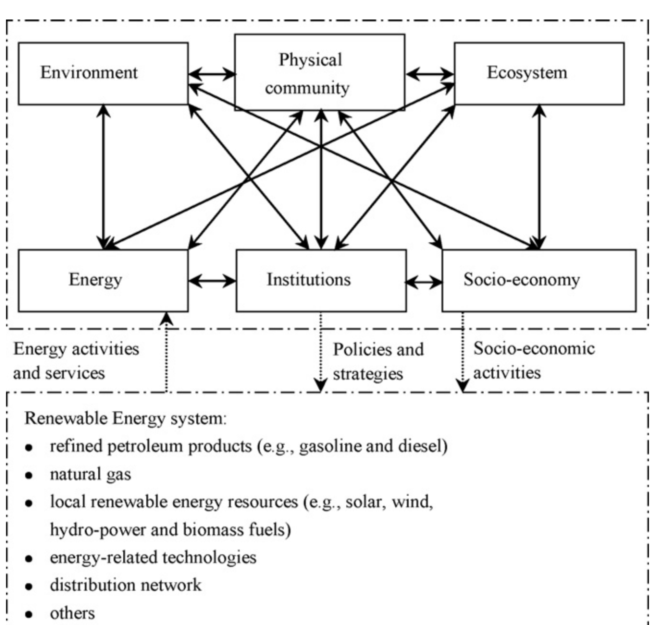

Fig. 1. Interactive relationships among different system components within a community.

Fig. 2 shows interactive relationships between different system sectors (energy production, processing, transmission and utilization) and relevant activities/services in a typical REM system. It is indicated that most of the activities are interrelated to each other. Any changes in one sector would lead to a series of consequences to and responses from the others, resulting in variations in system cost. In planning such a REM system, individual or independent consideration of one or several sectors would not be able to completely reflect the general system characteristics. This means that a satisfactory plan for one or several sectors may not be satisfactory for the entire system if some significant factors/components are neglected. Therefore, employment of optimization methods for REM systems planning would be essential for integrated reflection of the complex characteristics. At the same time, this figure implies interactive relationships among different system activities, with varying implications of energy-supply security and economic cost. Most of the activities are not only related to each other but also responsible to a number of economic costs and energy-supply security concerns. Thus, if there is any change in an activity, a series of consequences to the other activities and the related economic costs would be followed. For example, if local availabilities of renewable energy resources are insufficient to meet the energy demand, a certain degree of energy-supply risk may exist in the REM system. This may result in shifts of the existing technologies/resources over a long-term period and cause additional economic cost at relevant communities. However, between the activities and the related system costs and energy-supply risks, there may exist potential compromises which can lead to an optimal allocation of energy activities/services with satisfactory energy-supply security and minimized system cost. Consequently, in planning a REM system, systematic analysis of the related resources, environmental and socio-economic objectives/restriction based on projected applicable conditions should be undertaken.

In detail, characteristics of a REM system at a community level could be summarized as follows:

- *Multiple sources and technologies*. A single source of renewable energy is normally insufficient and unreliable for energy supply at communities due to its spatial/temporal fluctuations. In order to guarantee steady energy supply, multiple renewable energy sources should be adopted jointly in a REM system. Correspondingly, a multitude of relevant technologies are involved in such a system. These technologies are principally dominated by distributed electricity and thermal generation options (e.g., photovoltaic panels, micro-turbine systems, and micro-hydro). Thus, instability associated with an individual renewable energy

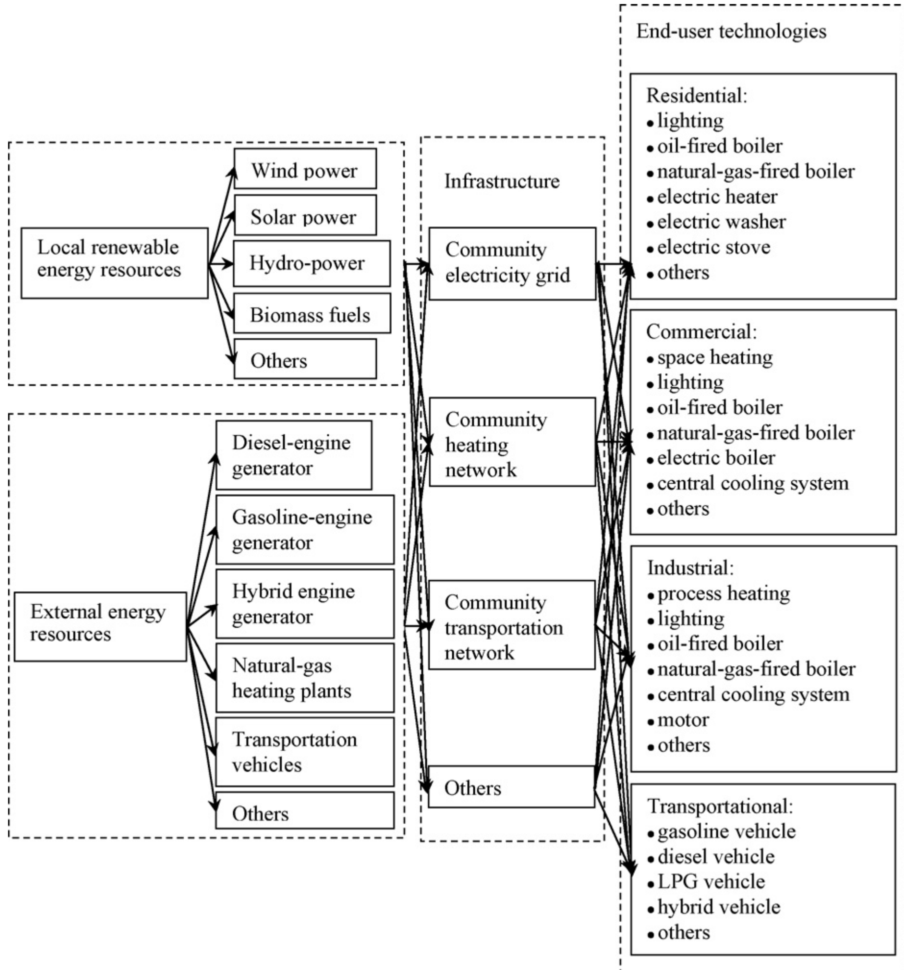

Fig. 2. Interactive relationships among different system components.

source can be circumvented through a combination of multiple ones. Energy-supply security can be highly enhanced, significantly lowering potential risks of energy insufficiency.

- *Multiple sectors and processes*. A number of sectors (e.g., energy supply and end-user demand) and processes (e.g., energy conversion and transmission), as well as their interactions, are contained in a REM system. Competitions and interactions may exist not only in each individual sector/process but also between each other (Fig. 2). For example, energy supply can be disaggregated into a variety of sub-sectors, such as electric power, industrial process steam, civil heating and others. The sub-sectors are comparatively independent with a certain degree of interactions; they are reflected by not only the competitions of energy-supply options with different economic and environmental performances, but also the availability of energy resources and the capacity limit of relevant technologies. Moreover, these interactions and competitions are further intensified by varying socio-economic, geographical, demographic and environmental conditions, as well as spatial and temporal distributions of energy sources.
- *Complexities and uncertainties*. Normally, renewable energy resources are intermittent and unreliable, which are subject to spatial and/or temporal fluctuations [63]. For example, availability and intensity of solar and wind energies are statistically uncertain, which can be expressed as probabilistic distributions. Also, these uncertainties are further complicated by a variety of imprecise information such as socio-economic, environmental and geographic conditions, energy carrier characteristics, energy prices, and demand projections. They can hardly be available as deterministic data. Thus, uncertainties may exist in multiple formats, leading to complexities in the relevant decision-making process.
- *Dynamic*. For the planning horizon, social, economic, legislational and resources conditions will vary with time. Reflection of such variations would be important for generating effective planning alternatives.

In general, energy activities/services within a community are related to a number of resources, environmental and socio-economic factors, as well as their interactions. Simple decision process based on direct analysis or expert consultation would not be satisfactory enough for effectively reflecting the system

complexities. Therefore, development of suitable systems analysis approaches to integrate a variety of components (objectives, constraints and activities) into a general modeling framework would be necessary. The systems analysis methods should be able to reflect interactive, complex, dynamic and uncertain features of the REM systems. Its outputs would be interpreted to generate desired planning alternatives for a number of human activities, as well as the relevant policies and strategies.

3. Community-scale energy systems planning model

Consider a community-scale REM system wherein a decision maker is responsible for allocating energy resources/services from multiple facilities to multiple sectors through multiple technologies within a multi-period horizon. The decision maker can formulate the problem as minimizing the expected value of net system cost with optimized capacity-expansion planning schemes and resources allocation patterns. In an integrated REM system, a number of facilities/technologies are available for energy production, conversion, transmission and utilization. For example, there are two types of technologies for power generation, including those utilizes renewable energy resources, as well as fossil fuel-based backups. Based on various policies, demand projections for every end-use sector can be obtained. The facilities in the REM system have overall-cumulative limits while the energy-demand amounts from the communities are flexible. Normally, if the demand does not exceed capacity limits of corresponding facilities, it will result in a regular cost. Otherwise, capacity expansions would be considered, resulting in an extra cost to the system. Thus, in the REM system, decision maker is to identify desired energy-flow allocation and facility-expansion schemes with a minimized system cost and a maximize system reliability. Therefore, the community-scale energy model (CS-EM) based on the MILP approach can be developed to address the planning problem. It can be characterized as a network/chain of energy flows, starting from energy supply options (such as energy productions and imports) and ending at end-use sectors (such as residential and commercial sectors). The objective is to minimize net system cost, which is related to energy flows from supply side to demand one. The decision variables represent key discrete points in the system, such as capacities of facilities, volumes of crude oil production, and gasoline consumed by vehicles. The constraints are a number of inequalities to define relationships among various decision variables and system conditions. In detail, costs of energy processing/supply and capacity expansion are considered in CS-EM. Thus, the objective function of CS-EM can be formulated as a sum of the following:

(a) costs for primary energy supply:

$$\sum_{t=1}^{3}(\mathrm{PD}_t\,X_{1,t}+\mathrm{PG}_t\,X_{2,t}+\mathrm{PN}_t\,X_{3,t}) \tag{1a}$$

(b) fixed and variable costs for power generation:

$$\sum_{m=1}^{3}\sum_{t=1}^{3}(\mathrm{VH}_{m,t}\,Y_{1,m,t}+\mathrm{VS}_{m,t}\,Y_{2,m,t}+\mathrm{VW}_{m,t}\,Y_{3,m,t}+\mathrm{VD}_{m,t}\,Y_{4,m,t}+\mathrm{VG}_{m,t}\,Y_{5,m,t}) \tag{1b}$$

(c) capital costs for capacity expansions of power-generation facilities:

$$\sum_{n=1}^{3}(\mathrm{IH}_n\,\mathrm{EH}_n\,Z_{1,n}+\mathrm{IS}_n\,\mathrm{ES}_n\,Z_{2,n}+\mathrm{IW}_n\,\mathrm{EW}_n\,Z_{3,n}) \tag{1c}$$

The constraints are listed as follows:

(a) mass balance:

$$\sum_{m=1}^{3}\mathrm{DTD}_{m,t}+\sum_{m=1}^{3}\mathrm{FED}_{m,t}\,Y_{4_{m,t}}\le X_{1,t},\quad \forall t \tag{1d}$$

$$\sum_{m=1}^{3}\mathrm{DTG}_{m,t}+\sum_{m=1}^{3}\mathrm{FEG}_{m,t}\,Y_{5_{m,t}}\le X_{2,t},\quad \forall t \tag{1e}$$

$$\sum_{m=1}^{3}\mathrm{DIN}_{m,t}+\sum_{m=1}^{3}\mathrm{DMN}_{m,t}\le X_{3,t},\quad \forall t \tag{1f}$$

(b) availabilities of energy resources:

$$\sum_{m=1}^{3}\left(\frac{Y_{1,m,t}}{\mathrm{FEH}_{m,t}}\right)\le \mathrm{AVH}_t,\quad \forall t \tag{1g}$$

$$\sum_{m=1}^{3}\left(\frac{Y_{2,m,t}}{\mathrm{FES}_{m,t}}\right)\le \mathrm{AVS}_t,\quad \forall t \tag{1h}$$

$$\sum_{m=1}^{3}\left(\frac{Y_{3,m,t}}{\mathrm{FEW}_{m,t}}\right)\le \mathrm{AVW}_t,\quad \forall t \tag{1i}$$

(c) electricity demand:

$$\sum_{m=1}^{3}(Y_{1,m,t}+Y_{2,m,t}+Y_{3,m,t}+Y_{4,m,t}+Y_{5,m,t})\ge\sum_{m=1}^{3}(\mathrm{DIE}_{m,t}+\mathrm{DME}_{m,t}+\mathrm{DAE}_{m,t}),\quad \forall t \tag{1j}$$

(d) capacity limits for power-generation facilities:

$$\sum_{n=1}^{3}(\mathrm{RCH}+Z_{1,n}\,\mathrm{EH}_n)\,\mathrm{UCAP}\ge\sum_{t=1}^{3}\sum_{m=1}^{3}Y_{1,m,t} \tag{1k}$$

$$\sum_{n=1}^{3}(\mathrm{RCS}+Z_{2,n}\,\mathrm{ES}_n)\,\mathrm{UCAP}\ge\sum_{t=1}^{3}\sum_{m=1}^{3}Y_{2,m,t} \tag{1l}$$

$$\sum_{n=1}^{3}(\mathrm{RCW}+Z_{3,n}\,\mathrm{EW}_n)\,\mathrm{UCAP}\ge\sum_{t=1}^{3}\sum_{m=1}^{3}Y_{3,m,t} \tag{1m}$$

(e) technical constraints:

$$X_{i,t}\ge 0,\quad \forall i,t \tag{1n}$$

$$Y_{j,m,t}\ge 0,\quad \forall j,m,t \tag{1o}$$

$$Z_{3,n}\ge 0,\quad \forall n \tag{1p}$$

(f) capacity limits for conventional (backup) power generators:

$$Y_{4,m,t} \leq \mathrm{UP}_{4,m,t}, \quad \forall t, m \tag{1q}$$

$$Y_{5,m,t} \leq \mathrm{UP}_{5,m,t}, \quad \forall t, m \tag{1r}$$

where $X_{1,t}$ is the diesel supply in period t (TJ); PD_t average cost for diesel supply in period t (\$$10^3$/TJ); $X_{2,t}$ gasoline supply in period t (TJ); PG_t average cost for domestic gasoline in period t (\$$10^3$/TJ); $X_{3,t}$ natural gas supply in period t (TJ); PN_t average cost for domestic natural gas supply in period t (\$$10^3$/TJ); $Y_{1,m,t}$ power from micro-hydro of community m in period t (MW); $\mathrm{VH}_{m,t}$ average variable and maintenance costs for hydro power of community m in period t (\$$10^3$/MW); $Y_{2,m,t}$ electricity from solar energy of community m in period t (MW); $\mathrm{VS}_{m,t}$ average variable and maintenance costs for solar energy to electricity of community m in period t (\$$10^3$/MW); $Y_{3,m,t}$ electricity generation from wind energy of community m in period t (MW); $\mathrm{VW}_{m,t}$ average variable and maintenance costs for wind energy to electricity of community m in period t (\$$10^3$/MW); $Y_{4,m,t}$ diesel as backup to electricity of community m in period t (MW); $\mathrm{VD}_{m,t}$ average variable and maintenance costs for diesel to electricity of community m in period t (\$$10^3$/MW); $Y_{5,m,t}$ gasoline as backup to electricity of community m in period t (MW); $\mathrm{VG}_{m,t}$ average variable and maintenance costs for gasoline to electricity (\$$10^3$/MW); $Z_{1,n}$ binary variables for capacity expansion of micro-hydro plant with expansion option n (MW); IH_n capital cost for capacity expansion of micro-hydro with expansion option n within the planning horizon (\$$10^3$/MW); EH_n capacity expansion options for micro-hydro within the planning horizon (MW); $Z_{2,n}$ binary variables for capacity expansion of solar energy to electricity with expansion option n (MW); IS_n capital cost for capacity expansion of solar energy to electricity with expansion option n within the planning horizon (\$$10^3$/MW); ES_n capacity expansion options for solar energy to electricity within the planning horizon (MW); $Z_{3,n}$ binary variables for capacity expansion of wind power to electricity with expansion option n (MW); IW_n capital cost for capacity expansion of wind power to electricity with expansion option n within the planning horizon (\$$10^3$/MW); EW_n capacity expansion options for wind power to electricity within the planning horizon (MW); $\mathrm{DTD}_{m,t}$ diesel demand for transportation of community m in period t (TJ); $\mathrm{DTG}_{m,t}$ gasoline demand of community m in period t (TJ); $\mathrm{DIN}_{m,t}$ natural gas demand for industrial sector of community m in period t (TJ); $\mathrm{DMN}_{m,t}$ natural gas demand for municipal/commercial sector of community m in period t (TJ); $\mathrm{DIE}_{m,t}$ electricity demand for industrial sector of community m in period t (TJ); $\mathrm{DME}_{m,t}$ electricity demand for municipal/commercial sector of community m in period t (TJ); $\mathrm{DAE}_{m,t}$ electricity demand for agricultural sector of community m in period t (TJ); $\mathrm{FED}_{m,t}$ conversion ratios from diesel to electricity of community m in period t; $\mathrm{FEG}_{m,t}$ conversion ratios from gasoline to electricity of community m in period t; $\mathrm{FEH}_{m,t}$ conversion ratios from hydropower to electricity of community m in period t; $\mathrm{FES}_{m,t}$ conversion ratios from solar energy to electricity of community m in period t; $\mathrm{FEW}_{m,t}$ conversion ratios from wind energy to electricity of community m in period t; RCH residual capacity for micro-hydro (MW); RCS residual capacity for solar energy to electricity (MW); RCW residual capacity for wind power to electricity (MW); $\mathrm{UP}_{4,m,t}$ upper bound for diesel as backup to electricity of m community in period t (MW); $\mathrm{UP}_{5,m,t}$ upper bound for gasoline as backup to electricity of m community in period t (MW) UCAP conversion coefficient for power generation capacity to energy; m index for communities ($m = 1$, 2 and 3); t index for time period ($t = 1$, 2, and 3); n is the capacity expansion options ($n = 1$, 2, and 3).

The above CS-EM model can effectively handle complexities that exist not only within an individual sector/process but also between each other in a REM system. Competitions among energy sources, power-generation technologies and resource availabilities can be reflected. Capacity expansion issues can also be addressed. However, CS-EM cannot reflect multiple forms of uncertainties, such as intervals and/or probability density functions (PDFs). For example, availabilities of many renewable energy resources (e.g., solar and wind energies) cannot be expressed in deterministic values; instead, they can be presented as probabilistic distributions [63]. At the same time, for most of socio-economic factors in a REM system (e.g., energy prices, demand projections and capital investment costs), it is impractical and onerous to acquire PDFs. Instead, they may be expressed in intervals. Different formats of uncertainties thus exist in the decision-making process, which should be incorporated within the formulation of CS-EM.

In order to address the above uncertainties (intervals and PDFs), the ILP and CCP methods are incorporated within CS-EM. ILP is an effective method for dealing with uncertainties existing as interval values without distribution information [56]. An interval number ($a^{\pm}$) can be expressed as [a^-, a^+], representing a number (or an interval) which can have a maximum value of a^+ and a minimum one of a^- [53]. A set of basic definitions for interval numbers was described in Huang et al. [53]. An interactive solution process was developed by Huang et al. to solve the ILP model [54,55]. However, ILP cannot deal with uncertainties expressed as probabilistic distributions, such as availability of renewable energy resources. CCP, which can handle uncertainties that exist as random information, can thus be integrated with ILP, leading to an inexact community-scale energy systems model (ICS-EM). Multiple forms of uncertainties in CS-EM can thus be tackled. According to Huang et al., an ILP model integrated with CCP can be written as follows [9,54]:

$$\mathrm{Min}\ f^{\pm} = C^{\pm}X^{\pm} \tag{2a}$$

subject to:

$$A^{\pm}X^{\pm} \leq B^{p_i^{\pm}} \quad (2b)$$

$$X^{\pm} \geq 0 \quad (2c)$$

where $A^{\pm} \in \{R^{\pm}\}^{m\times n}$, $C^{\pm} \in \{R^{\pm}\}^{1\times n}$, $X^{\pm} \in \{R^{\pm}\}^{n\times 1}$, and $R^{\pm}$ denotes a set of interval numbers, $B^{\pm} \in \{R^{p_i^{\pm}}\}^{m\times 1}$, p_i denotes a series of probability levels for the parameter.

Based on the above methods, ICS-EM can be formulated with its parameters being intervals and/or probabilistic distributions. According to solution algorithm developed by Huang et al., the ICS-EM model can be solved through analyzing interrelationships between the parameters and the variables, and between the objective function and the constraints [9,53–55]. Solutions are obtained through a two-step method, where a sub-model corresponding to f^- (when the objective function is to be minimized) is firstly formulated, and then the relevant sub-model corresponding to f^+ can be obtained based on the solution of the first sub-model. The two sub-models are presented as follows:

(a) sub-model 1,

$$\begin{aligned} f^- = {} & \sum_{t=1}^{3}(\mathrm{PD}_t^- X_{1,t}^{-\leq} + \mathrm{PG}_t^- X_{2,t}^- + \mathrm{PN}_t^- X_{3,t}^-) \\ & + \left(\sum_{m=1}^{3}\sum_{t=1}^{3}\mathrm{VH}_{m,t}^- Y_{1,m,t}^- + \mathrm{VS}_{m,t}^- Y_{2,m,t}^- \right. \\ & \left. + \mathrm{VW}_{m,t}^- Y_{3,m,t}^- + \mathrm{VD}_{m,t}^- Y_{4,m,t}^- + \mathrm{VG}_{m,t}^- Y_{5,m,t}^-\right) \\ & + \left(\sum_{t=1}^{3}\sum_{n=1}^{3}\mathrm{IH}^- \mathrm{EH}_n^- Z_{1,n}^- + \mathrm{IS}^- \mathrm{ES}_n^- Z_{2,n}^- \right. \\ & \left. + \mathrm{IW}^- \mathrm{EW}_n^- Z_{3,n}^-\right) \end{aligned} \quad (3a)$$

subject to:

$$\sum_{m=1}^{3}\mathrm{FED}_{m,t}^+ Y_{4,m,t}^- - X_{1,t}^- \leq -\sum_{m=1}^{3}\mathrm{DTD}_{m,t}^-, \quad \forall t \quad (3b)$$

$$\sum_{m=1}^{3}\mathrm{FEG}_{m,t}^+ Y_{5,m,t}^- - X_{2,t}^- \leq -\sum_{m=1}^{3}\mathrm{DTG}_{m,t}^-, \quad \forall t \quad (3c)$$

$$\sum_{m=1}^{3}\mathrm{DIN}_{m,t}^- + \sum_{m=1}^{3}\mathrm{DMN}_{m,t}^- \leq X_{3,t}^-, \quad \forall t \quad (3d)$$

$$\sum_{m=1}^{3}\frac{Y_{3,m,t}^-}{\mathrm{FEH}_{m,t}^-} \leq \mathrm{AVH}_t^+, \quad \forall t \quad (3e)$$

$$\sum_{m=1}^{3}\frac{Y_{4,m,t}^-}{\mathrm{FES}_{m,t}^-} \leq \mathrm{AVS}_t^{+(p_i)}, \quad \forall t \quad (3f)$$

$$\sum_{m=1}^{3}\frac{Y_{5,m,t}^-}{\mathrm{FEW}_{m,t}^-} \leq \mathrm{AVW}_t^{+(p_i)}, \quad \forall t \quad (3g)$$

$$\begin{aligned} & \sum_{m=1}^{3}(Y_{1,m,t}^- + Y_{2,m,t}^- + Y_{3,m,t}^- + Y_{4,m,t}^- + Y_{5,m,t}^-) \geq \mathrm{DIE}_t^- \\ & \quad + \mathrm{DME}_t^- + \mathrm{DAE}_t^-, \quad \forall t \end{aligned} \quad (3h)$$

$$\mathrm{RCH}^-\,\mathrm{UCAP} \geq \sum_{t=1}^{3}\sum_{m=1}^{3}Y_{1,m,t}^- - \mathrm{UCAP}\sum_{n=1}^{3}Z_{1,n}^-\,\mathrm{EH}_n^+ \quad (3i)$$

$$\mathrm{RCS}^-\,\mathrm{UCAP} \geq \sum_{t=1}^{3}\sum_{m=1}^{3}Y_{2,m,t}^- - \mathrm{UCAP}\sum_{n=1}^{3}Z_{2,n}^-\,\mathrm{ES}_n^+ \quad (3j)$$

$$\mathrm{RCW}^-\,\mathrm{UCAP} \geq \sum_{t=1}^{3}\sum_{m=1}^{3}Y_{3,m,t}^- - \mathrm{UCAP}\sum_{n=1}^{3}Z_{3,n}^-\,\mathrm{EW}_n^+ \quad (3k)$$

$$Y_{4,m,t}^- \leq \mathrm{UP}_{4,m,t}^+, \quad \forall t, m \quad (3l)$$

$$Y_{5,m,t}^- \leq \mathrm{UP}_{5,m,t}^+, \quad \forall t, m \quad (3m)$$

Through sub-model ((3a)–(3m)), solutions of $(X_{i,t}^-)_{\mathrm{opt}}$ (i = 1, 2, 3; t = 1, 2, 3), $(Y_{j,m,t}^-)_{\mathrm{opt}}$ (j = 1, 2, 3; m = 1, 2, 3; t = 1, 2, 3), and $(Z_{k,n}^-)_{\mathrm{opt}}$ (k = 1, 2, 3; n = 1, 2, 3) can be obtained under different p_i levels. Thus, the sub-model corresponding to f^+ can be formulated as follows (assuming that $b_i^{\pm} > 0$, and $f^{\pm} > 0$):

(b) sub-model 2,

$$\begin{aligned} f^+ = {} & \sum_{m=1}^{3}(\mathrm{PD}_t^+ X_{1,t}^+ + \mathrm{PG}_t^+ X_{2,t}^+ + \mathrm{PN}_t^+ X_{3,t}^+) \\ & + \left(\sum_{m=1}^{3}\sum_{t=1}^{3}\mathrm{VH}_{m,t}^+ Y_{1,m,t}^+ + \mathrm{VS}_{m,t}^+ Y_{2,m,t}^+ + \mathrm{VW}_{m,t}^+ Y_{3,m,t}^+ \right. \\ & \left. + \mathrm{VD}_{m,t}^+ Y_{4,m,t}^+ + \mathrm{VG}_{m,t}^+ Y_{5,m,t}^+\right) \\ & + \left(\sum_{t=1}^{3}\sum_{n=1}^{3}\mathrm{IH}^+ \mathrm{EH}_n^+ Z_{1,n}^+ + \mathrm{IS}^+ \mathrm{ES}_n^+ Z_{2,n}^+ \right. \\ & \left. + \mathrm{IW}^+ \mathrm{EW}_n^+ Z_{3,n}^+\right) \end{aligned} \quad (4a)$$

subject to:

$$\sum_{m=1}^{3}\mathrm{FED}_{m,t}^- Y_{4,m,t}^+ - X_{1,t}^+ \leq -\sum_{m=1}^{3}\mathrm{DTD}_{m,t}^+, \quad \forall t \quad (4b)$$

$$\sum_{m=1}^{3}\mathrm{FEG}_{m,t}^- Y_{5,m,t}^+ - X_{2,t}^+ \leq -\sum_{m=1}^{3}\mathrm{DTG}_{m,t}^+, \quad \forall t \quad (4c)$$

$$\sum_{m=1}^{3}\mathrm{DIN}_{m,t}^+ + \sum_{m=1}^{3}\mathrm{DMN}_{m,t}^+ \leq X_{3,t}^+, \quad \forall t \quad (4d)$$

$$\sum_{m=1}^{3}\frac{Y_{3,m,t}^+}{\mathrm{FEH}_{m,t}^+} \leq \mathrm{AVH}_t^-, \quad \forall t \quad (4e)$$

$$\sum_{m=1}^{3} \frac{Y_{4,m,t}^{+}}{\mathrm{FES}_{m,t}^{+}} \leq \mathrm{AVS}_t^{-(p_i)}, \quad \forall t \tag{4f}$$

$$\sum_{m=1}^{3} \frac{Y_{5,m,t}^{+}}{\mathrm{FEW}_{m,t}^{+}} \leq \mathrm{AVW}_t^{-(p_i)}, \quad \forall t \tag{4g}$$

$$\sum_{m=1}^{3} (Y_{1,m,t}^{+} + Y_{2,m,t}^{+} + Y_{3,m,t}^{+} + Y_{4,m,t}^{+} + Y_{5,m,t}^{+}) \geq \mathrm{DIE}_t^{+} + \mathrm{DME}_t^{+} + \mathrm{DAE}_t^{+}, \quad \forall t \tag{4h}$$

$$\mathrm{RCH}^{+}\,\mathrm{UCAP} \geq \sum_{t=1}^{3}\sum_{m=1}^{3} Y_{1,m,t}^{+} - \mathrm{UCAP}\sum_{n=1}^{3} Z_{1,n}^{+}\,\mathrm{EH}_n^{-} \tag{4i}$$

$$\mathrm{RCS}^{+}\,\mathrm{UCAP} \geq \sum_{t=1}^{3}\sum_{m=1}^{3} Y_{2,m,t}^{+} - \mathrm{UCAP}\sum_{n=1}^{3} Z_{2,n}^{+}\,\mathrm{ES}_n^{-} \tag{4j}$$

$$\mathrm{RCW}^{+}\,\mathrm{UCAP} \geq \sum_{t=1}^{3}\sum_{m=1}^{3} Y_{3,m,t}^{+} - \mathrm{UCAP}\sum_{n=1}^{3} Z_{3,n}^{+}\,\mathrm{EW}_n^{-} \tag{4k}$$

$$Y_{4,m,t}^{+} \leq \mathrm{UP}_{4,m,t}^{-}, \quad \forall t, m \tag{4l}$$

$$Y_{5,m,t}^{+} \leq \mathrm{UP}_{5,m,t}^{-}, \quad \forall t, m \tag{4m}$$

$$X_{i,t}^{+} \geq (X_{i,t}^{-})_{\mathrm{opt}} \tag{4n}$$

$$Y_{j,m,t}^{+} \geq (Y_{j,m,t}^{-})_{\mathrm{opt}} \tag{4o}$$

$$Z_{k,n}^{+} \geq (Z_{k,n}^{-})_{\mathrm{opt}} \tag{4p}$$

$$f^{+} \geq f_{\mathrm{opt}}^{-} \tag{4q}$$

Hence, solutions of f_{opt}^{+}, $(X_{i,t}^{+})_{\mathrm{opt}}$ (i = 1, 2, 3; t = 1, 2, 3), $(Y_{j,m,t}^{+})_{\mathrm{opt}}$ (j = 1, 2, 3; m = 1, 2, 3; t = 1, 2, 3), and $(Z_{k,n}^{+})_{\mathrm{opt}}$ (k = 1, 2, 3; n = 1, 2, 3) can be obtained through solving sub-model ((4a)–(4q)). Thus, we can have the final solution of $f_{\mathrm{opt}}^{\pm} = [f_{\mathrm{opt}}^{-}, f_{\mathrm{opt}}^{+}]$, and $(X_{i,t}^{\pm})_{\mathrm{opt}} = [(X_{i,t}^{-})_{\mathrm{opt}}, (X_{i,t}^{+})_{\mathrm{opt}}]$, $(Y_{j,m,t}^{\pm})_{\mathrm{opt}} = [(Y_{j,m,t}^{-})_{\mathrm{opt}}, (Y_{j,m,t}^{+})_{\mathrm{opt}}]$ and $(Z_{k,n}^{\pm})_{\mathrm{opt}} = [(Z_{k,n}^{-})_{\mathrm{opt}}, (Z_{k,n}^{+})_{\mathrm{opt}}]$.

Apparently, ICS-EM improves upon the conventional methods by incorporating multiple forms of uncertainties within a general framework based on an integration of ILP, CCP and MILP. It can handle uncertainties presented as interval values, probabilistic distributions and their combinations; also, it can also facilitate dynamic analysis (e.g., capacity expansion planning) under uncertainty. Multiple forms of uncertainties, which origin from a number of sources (such as natural availabilities of renewable resources, socio-economic conditions and locations of communities), can be reflected as intervals and PDFs. ICS-EM can thus be used for analyzing a variety of energy-related policy scenarios that are associated with different economic and social effects. System reliability and energy-supply security can be reflected. In detail, it has three advantages of ICS-EM: (a) it can tackle uncertainties in both left- and right-hand side coefficients expressed as probability distributions and/or interval values, (b) it can be used for examining various scenarios that are associated with different levels of system-violation risks (energy-supply security), and (c) it can facilitate dynamic analyses of capacity-expansion decisions under uncertainty.

4. Case study

The following REM problem is used to demonstrate applicability of the developed ICS-EM model. In the study system, multiple renewable energy resources/technologies need to be allocated to multiple end users at one or several communities. The end users are decomposed into agricultural, transportation, industrial, and municipal/commercial sectors. Conventional and renewable energy resources (e.g., diesel, gasoline, natural gas, solar, wind and hydropower) with limited availabilities are employed for meeting the energy demands. In detail, diesel and gasoline are mainly used for transportation activities, while part of them is used for power generation as backups [49,64–66]. Natural gas is used for municipal and industrial heat production. Renewable energy resources are mainly employed for power generation. Once these energy sources are determined, costs, efficiencies and capacities of corresponding technologies can be defined. Conversion and processing technologies mainly include those for large-scale heat generation, as well as small-scale renewable-based ones. Small-scale technologies largely dominate electricity production from local renewable energy resources. If energy supply cannot sufficiently meet end-user demands, decision-makers will face a dilemma of either investing more funds on capacity expansion of existing facilities or turning to other energy production options with higher costs. Availabilities of renewable energy resources are directly affected by their natural fluctuations, which can be presented as probability distributions. Thus, parameters of their availabilities are expressed as PDFs (normal and/or Weybull distributions) [49,65,67–69]. Most of the other parameters (such as energy demand, technological efficiency and utilization factors) are expressed as intervals without distribution information.

The study system is comprised of three typical communities, which have varied economic and environmental costs for renewable energy supply and power generation. Conventional and renewable energy resources, relevant technologies and multiple end-use sectors are included in the study system (Fig. 3). Three time periods are considered, with each having an interval of 5 years. Over the 15-year planning horizon, an existing renewable power generation system is available to meet electricity needs of the three communities. Facilities of micro-hydro, solar energy, and wind farm are available in the sub-system of power generation. Also, small-scale fossil fuel-based (e.g., gasoline and diesel) power generation units are installed as emergency backups. Probability distributions for the availabilities of solar and wind energies are presented in Table 1 (under different p_i levels). Average costs of energy supply, capital investment and capacity expansion are shown in

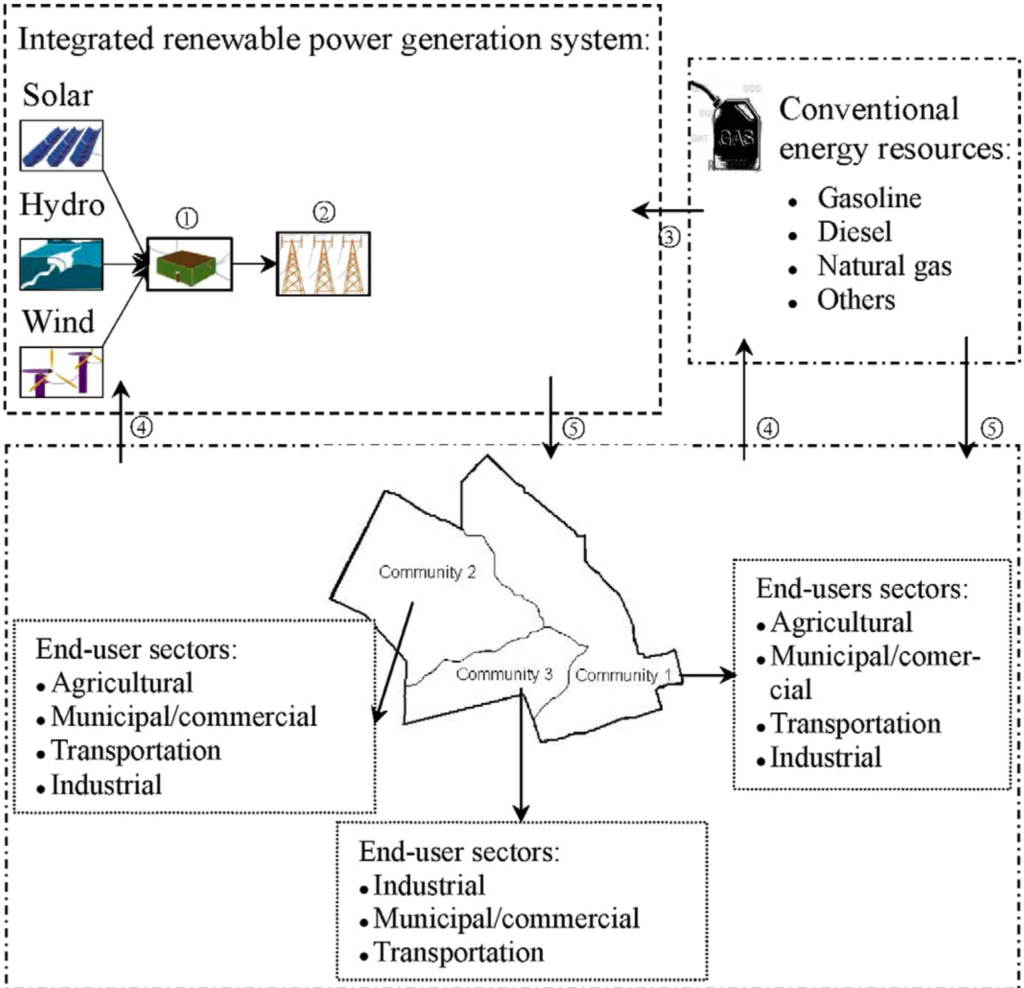

Fig. 3. The study system. *Note*: ① power conditioner and controller; ② local power distribution system; ③ conventional power-generation facilities; ④ policies, strategies and regulations; ⑤ energy supply.

Table 2. Table 3 shows end-user demands from agricultural, industrial, municipal and transportation sectors.

Solutions of the ICS-EM model are displayed in Tables 4 and 6 (under three p_i levels). Several assumptions are made for the ICS-EM model, including (a) normal distribution is given to the availability of solar energy, (b) the availability of wind energy is expressed as Weybull distribution, (c) capacity expansion of each facility is limited to once within the planning horizon, and (d) economic and energy structures of the three communities are different from each other.

The results indicate that energy production and consumption patterns at the three communities are similar to each other. However, the total system cost would vary slightly, reflecting interrelationships among economic cost, energy-supply security and system reliability (risks of constraint violation). Different p_i values represent different violation levels. Higher p_i values would lead to a higher probability of constraint violation, and thus give rise to a lower system cost. When the availabilities of renewable energy resources are limited, more electricity would be generated from conventional facilities,

Table 1
Renewable energy availabilities under different p_i values (wind and solar energies)

	p_i value													
	0.01	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95	0.99	1.00
Wind energy availability (TJ)														
Upperbound	8.83	9.80	10.43	11.30	12.00	12.63	13.25	13.89	14.60	15.43	16.61	17.56	19.16	20.30
Lowerbound	8.43	8.95	9.33	9.93	10.43	10.92	11.41	11.93	12.53	13.26	14.33	15.22	16.78	17.93
Solar energy availability (TJ)														
Upperbound	4.47	4.91	5.10	5.33	5.49	5.62	5.75	5.88	6.01	6.17	6.38	6.55	6.84	7.04
Lowerbound	4.05	4.44	4.62	4.82	4.96	5.09	5.20	5.31	5.43	5.58	5.77	5.92	6.18	6.36

Table 2
Capital costs and capacity-expansion options for power-generation facilities

	Time period		
	$k=1$	$k=2$	$k=3$
Capacity expansion options (MW)			
Small-hydro	0.3	0.3	0.3
	0.4	0.4	0.4
	0.5	0.5	0.5
Solar	0.05	0.05	0.05
	0.075	0.075	0.075
	0.1	0.1	0.1
Wind	0.075	0.075	0.075
	0.1	0.1	0.1
	0.125	0.125	0.125
Capital cost ($\$10^3$/MW)			
Small-hydro	[2916.0, 3564.0]	[2482.0, 3034.0]	[1932.0, 2362.0]
Solar	[3150.0, 3850.0]	[2700.0, 3300.0]	[2250.0, 2750.0]
Wind	[1318.0, 1611.0]	[1223.0, 1495.0]	[1150.0, 1406.0]

leading to a higher system cost. In detail, as indicated in Tables 4 and 5, supply patterns of the conventional energy resources (diesel, gasoline and natural gas) are almost the same under the three p_i levels except for diesel supply. Minor variations would be observed for diesel supply, representing that renewable energy resources would be insufficient for meeting the electricity demands under demanding conditions. Under the three p_i levels, energy demands from each community and its corresponding sectors would be comparatively stable. Direct demand for fossil fuel (including diesel, gasoline and natural gas) would increase steadily over the planning horizon due to economic development, population growth and living-standard improvement. For the three communities, diesel supply over the three periods would be [4.8, 5.0], [5.2, 5.4] and [25.09, 25.09] TJ when p_i equals 0.01, [4.8, 5.0], [5.2, 5.4] and [8.9, 8.9] TJ when p_i equals 0.05, and [4.8, 5.0], [5.2, 5.4] and [5.6, 5.8] TJ when p_i equals 0.1, respectively. Comparatively, gasoline supply during the three periods would be [5.5, 5.8], [6.3, 6.6] and [6.5, 6.8] TJ, respectively. Natural gas supply would be [12.0, 14.0], [12.3, 14.3] and [12.9, 14.9] TJ in periods 1, 2 and 3, respectively. The total costs for energy supply, power generation and energy consumptions would be $\$[955.3, 1218.3] \times 10^3$, $[778.5, 1005.7] \times 10^3$, $[743.9, 965.7] \times 10^3$, under $p_i = 0.01$, 0.05, and 0.1, respectively. Most of the electricity would be generated from renewable energy resources, i.e., hydropower, wind and solar energies. Also, a minor part of energy supply (especially for electricity) would be from fossil fuel backups. The power generation patterns would be relatively stable, being [68.4, 74.3] TJ (including [33.7, 33.8], [35.7, 40.5], [9.5, 9.5] and 0 TJ from micro-hydro, solar, wind and diesel backup generators, respectively) when $p_i = 0.01$ in period 1; in periods 2 and 3, [84.9, 89.7] and [99.8, 104.7] TJ of electricity would be generated, respectively. Similar power-generation patterns would also exist under the other two p_i levels. However, electricity from fossil fuel would decrease gradually when the p_i levels are increased from 0.01 to 0.1. Furthermore, the

Table 3
End-user demands (TJ)

	Time period		
	$k=1$	$k=2$	$k=3$
Community 1			
T			
Diesel	[7.25, 7.55]	[7.84, 8.14]	[8.48, 8.78]
Gasoline	[8.29, 8.74]	[9.45, 9.90]	[9.75, 10.20]
I			
Natural gas	[18.45, 21.45]	[19.18, 22.18]	[19.95, 22.95]
Electricity	[1.82, 1.92]	[2.35, 2.45]	[2.88, 2.98]
A			
Natural gas	[0, 0]	[0, 0]	[0, 0]
Electricity	[3.16, 3.41]	[3.70, 3.95]	[4.21, 4.46]
MC			
Natural gas	[17.26, 20.27]	[17.75, 20.75]	[18.54, 21.54]
Electricity	[1.26, 1.36]	[1.48, 1.58]	[1.68, 1.78]
Community 2			
T			
Diesel	[12.08, 12.58]	[13.07, 13.57]	[14.13, 14.63]
Gasoline	[13.82, 14.57]	[15.75, 16.50]	[16.25, 17.00]
I			
Natural gas	[12.30, 14.30]	[12.79, 14.79]	[13.30, 15.30]
Electricity	[5.46, 5.76]	[7.05, 7.35]	[8.64, 8.94]
A			
Natural gas	[0, 0]	[0, 0]	[0, 0]
Electricity	[9.47, 10.22]	[11.09, 11.84]	[12.62, 13.37]
MC			
Natural gas	[11.51, 13.51]	[11.83, 13.83]	[12.36, 14.36]
Electricity	[3.79, 4.09]	[4.43, 4.73]	[5.05, 5.35]
Community 3			
T			
Diesel	[28.99, 30.19]	[31.39, 32.57]	[33.90, 35.10]
Gasoline	[33.16, 34.96]	[37.81, 39.61]	[38.99, 40.79]
I			
Natural gas	[30.76, 35.76]	[31.97, 36.97]	[33.25, 38.25]
Electricity	[10.92, 11.52]	[14.10, 14.70]	[17.28, 17.88]
A			
Natural gas	[0, 0]	[0, 0]	[0, 0]
Electricity	[0, 0]	[0, 0]	[0, 0]
MC			
Natural gas	[28.78, 33.78]	[29.59, 34.59]	[30.90, 35.90]
Electricity	[7.57, 8.18]	[8.87, 9.49]	[10.10, 10.70]

Note: T, transportation; I, industrial; A, agricultural; MC, municipal and commercial.

capacity-expansion schemes would be stable, which means that capacities for converting renewable energy to electricity would be generally sufficient to meet electricity demand in the study communities. For wind-energy facilities, capacity expansion would occur with the first expansion option in period 3. This is because electricity demand in period 3 would be slightly higher than the total electricity-generation capacity, requiring expansion for one or several facilities. The results also indicate that the ICS-EM solutions can provide ranges of options for allocating energy resources/services and identifying corresponding system costs under different p_i values. For example,

Table 4
Continuous solutions for primary energy supplies

Primary energy supply (TJ)	Energy resources	Period	Solutions for different p_i values		
			0.01	0.05	0.1
$(X_{11})^{\pm}$	1	1	[4.8, 5.0]	[4.8, 5.0]	[4.8, 5.0]
$(X_{12})^{\pm}$	1	2	[5.2, 5.4]	[5.2, 5.4]	[5.2, 5.4]
$(X_{13})^{\pm}$	1	3	[25.09, 25.09]	[8.9, 8.9]	[5.6, 5.8]
$(X_{21})^{\pm}$	2	1	[5.5, 5.8]	[5.5, 5.8]	[5.5, 5.8]
$(X_{22})^{\pm}$	2	2	[6.3, 6.6]	[6.3, 6.6]	[6.3, 6.6]
$(X_{23})^{\pm}$	2	3	[6.5, 6.8]	[6.5, 6.8]	[6.5, 6.8]
$(X_{31})^{\pm}$	3	1	[12.0, 14.0]	[12.0, 14.0]	[12.0, 14.0]
$(X_{32})^{\pm}$	3	2	[12.3, 14.3]	[12.3, 14.3]	[12.3, 14.3]
$(X_{33})^{\pm}$	3	3	[12.9, 14.9]	[12.9, 14.9]	[12.9, 14.9]
$(f)^{\pm}$ ($\$10^3$)			[955.3, 1218.3]	[778.5, 1005.7]	[743.9, 965.7]

Table 5
Continuous solutions for power generation

Power generation	Energy resource	Community	Period	$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.1$
$(Y_{111})^{\pm}$	1	1	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{112})^{\pm}$	1	1	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{113})^{\pm}$	1	1	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{121})^{\pm}$	1	2	1	[33.7, 33.8]	[30.3, 30.3]	[13.8, 13.8]
$(Y_{122})^{\pm}$	1	2	2	[15.0, 15.0]	[18.5, 18.5]	[35.0, 35.0]
$(Y_{123})^{\pm}$	1	2	3	[30.0, 30.0]	[30.0, 30.0]	[30.0, 30.0]
$(Y_{131})^{\pm}$	1	3	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{132})^{\pm}$	1	3	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{133})^{\pm}$	1	3	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{211})^{\pm}$	2	1	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{212})^{\pm}$	2	1	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{213})^{\pm}$	2	1	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{221})^{\pm}$	2	2	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{222})^{\pm}$	2	2	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{223})^{\pm}$	2	2	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{231})^{\pm}$	2	3	1	[35.7, 40.5]	[39.2, 44.0]	[40.8, 45.6]
$(Y_{232})^{\pm}$	2	3	2	[31.3, 36.1]	[33.8, 38.6]	[33.3, 38.1]
$(Y_{233})^{\pm}$	2	3	3	[26.8, 31.6]	[29.4, 34.2]	[28.3, 33.1]
$(Y_{311})^{\pm}$	3	1	1	[0, 0]	[0, 0]	[14.9, 14.9]
$(Y_{312})^{\pm}$	3	1	2	[38.6, 38.6]	[32.6, 32.6]	[16.6, 16.6]
$(Y_{313})^{\pm}$	3	1	3	[35.3, 35.3]	[39.2, 39.2]	[41.6, 41.6]
$(Y_{321})^{\pm}$	3	2	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{322})^{\pm}$	3	2	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{323})^{\pm}$	3	2	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{331})^{\pm}$	3	3	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{332})^{\pm}$	3	3	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{333})^{\pm}$	3	3	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{411})^{\pm}$	4	1	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{412})^{\pm}$	4	1	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{413})^{\pm}$	4	1	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{421})^{\pm}$	4	2	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{422})^{\pm}$	4	2	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{423})^{\pm}$	4	2	3	[7.8, 7.8]	[1.3, 1.3]	[0, 0]
$(Y_{431})^{\pm}$	4	3	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{432})^{\pm}$	4	3	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{433})^{\pm}$	4	3	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{511})^{\pm}$	5	1	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{512})^{\pm}$	5	1	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{513})^{\pm}$	5	1	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{521})^{\pm}$	5	2	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{522})^{\pm}$	5	2	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{523})^{\pm}$	5	2	3	[0, 0]	[0, 0]	[0, 0]
$(Y_{531})^{\pm}$	5	3	1	[0, 0]	[0, 0]	[0, 0]
$(Y_{532})^{\pm}$	5	3	2	[0, 0]	[0, 0]	[0, 0]
$(Y_{533})^{\pm}$	5	3	3	[0, 0]	[0, 0]	[0, 0]

Table 6
Binary solutions for capacity expansions

Capacity expansion for power generation	Energy resources	Period	$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.1$
$Z_{11}^{\pm}$	1	1	[0, 0]	[0, 0]	[0, 0]
$Z_{12}^{\pm}$	1	2	[0, 0]	[0, 0]	[0, 0]
$Z_{13}^{\pm}$	1	3	[0, 0]	[0, 0]	[0, 0]
$Z_{21}^{\pm}$	2	1	[0, 0]	[0, 0]	[0, 0]
$Z_{22}^{\pm}$	2	2	[1, 1]	[1, 1]	[1, 1]
$Z_{23}^{\pm}$	2	3	[0, 0]	[0, 0]	[0, 0]
$Z_{31}^{\pm}$	3	1	[0, 0]	[0, 0]	[0, 0]
$Z_{32}^{\pm}$	3	2	[0, 0]	[0, 0]	[0, 0]
$Z_{33}^{\pm}$	3	3	[0, 0]	[0, 0]	[0, 0]

the solutions of $f^{\pm}$ under $p_i = 0.01$, 0.05, and 0.1 are \$[955.3, 1218.3] $\times 10^3$, [778.5, 1005.7] $\times 10^3$ and [743.9, 965.7] $\times 10^3$, respectively. When different allocating patterns are selected through shifting values of decision variables within their interval solutions, the corresponding system cost would change within its interval (Table 4).

As indicates in Tables 5 and 6, the most sensitive component in the REM system to explicit variations would be the power-generation subsystem. In real-world cases, the cost for electricity generation would be highly dependent upon the community's site-specific characteristics, which vary with political, geographical, legislational, economic and environmental conditions. Under favorable conditions (energy demand is lower than power-generation capacity), electricity-generation facilities with the lowest costs within the three communities would be adopted in the first place. Under demanding conditions (energy demand is higher than the power-generation capacity), power-generation options with higher costs would be adopted. For example, as micro-hydro, community 2 would be the most favorable area for power generation. In the three periods, power generation capacities of micro-hydro would be [33.7, 33.8], [15.0, 15.0], and [30.0, 30.0] TJ under a p_i value of 0.01, respectively. This pattern would also be stable under the other two p_i levels (i.e., [30.3, 30.3], [18.5, 18.5] and [30.0, 30.0] TJ under a p_i level of 0.05, and [13.8, 13.8], [35.0, 35.0] and [30.0, 30.0] TJ under a p_i level of 0.1, respectively). For communities 2 and 3, electricity generation from hydropower would be zero due to its higher costs for electricity production. Similar patterns also exist under the other two p_i values. For solar energy utilization, community 2 would be the most cost-effective area. Over the planning horizon, power generation from solar energy would be [35.8, 40.5], [31.3, 36.1] and [26.8, 31.6] TJ under $p_i = 0.01$; [39.2, 44.0], [33.8, 38.6] and [29.4, 34.2] under $p_i = 0.05$; and [40.8, 45.6], [33.3, 38.1] and [28.3, 33.1] under $p_i = 0.1$. Generally, under the three significance levels, the utilization of solar energy in communities 1 and 2 would both be zero, reflecting unfavorable situations in solar energy exploitation due to its high costs. Wind energy would be adopted in community 1. Over the three periods, power generation from wind energy would be 0, [38.6, 38.6], and [35.3, 35.3] TJ under $p_i = 0.01$. The same patterns would be observed under $p_i = 0.05$ (0, [32.6, 32.6], and [39.2, 39.2] TJ). Under $p_i = 0.1$, these values would become [14.9, 14.9], [16.6, 16.6], and [41.6, 41.6] TJ, respectively. Moreover, under extreme events (demanding conditions for renewable energy resources), fossil fuel-based backups for power generation would be activated. For example, power generation from fossil fuels (diesel) in community 3 would be [7.8, 7.8] TJ under $p_i = 0.01$, and [1.3, 1.3] TJ under $p_i = 0.05$. However, power generated from backups would be zero under $p_i = 0.1$ over the three periods, which means that electricity from renewable energy sources would be sufficient for meeting energy demands in the three communities. Also, the capacity for generating power from solar energy would be expanded firstly due to its relatively low capital costs for capacity expansion.

Different forms of uncertainties are successfully incorporated within the ICS-EM framework. When $p_i = 0.01$, a number of solutions for decision variables are intervals, while some remain as deterministic values. For example, diesel supplies in the three periods would amount to [4.8, 5.0], [5.2, 5.4], and [25.09, 25.09] TJ, respectively. In contrast, the amounts of electricity generation from hydropower in community 2 would be 33.7, 15.0, and 30.0 TJ, respectively. When $p_i = 0.01$, the system cost would be \$[955.3, 1218.3] $\times 10^3$. Most of the solutions are presented as interval numbers, facilitating the reflection of uncertainties during the decision-making process. Based on the interval solutions, multiple decision alternatives can be generated. Therefore, uncertain information can be effectively used by decision makers to adjust decision schemes and analyze tradeoffs between economic cost and energy-supply security. When a conservative strategy is adopted, a scheme corresponding to the upper bound of the objective value would be appropriate; however, when an optimistic strategy is adopted, a scheme corresponding to a lower objective value would be suitable.

Moreover, the solutions indicate that ICS-EM can reflect energy-supply security since the p_i values correspond to probability levels associated with the availabilities of renewable energy resources. This is because the REM system mainly employs renewable resources and is subject to risks when these resources are limited. The p_i values signify the risks of violating constraints for supplying renewable energy resources. The availabilities of renewable energy resources are also related to the total system cost. For example, with an increment of p_i value (i.e., increment of system violation level), the system cost

would decrease to achieve a more optimistic result. This implies that, when the p_i value successively increases (0.01, 0.05 and 0.1), the system cost would correspondingly decrease (\$[955.3, 1218.3] $\times 10^3$, [778.5, 1005.7] $\times 10^3$ and [743.9, 965.7] $\times 10^3$). Therefore, not only the tradeoffs between system costs and violation levels but also the probability distributions of energy availabilities can be integrated into the modeling process. The solutions provide a desired compromise among system optimality, energy-supply stability and system cost, and are thus a robust reflection of the system complexities and uncertainties.

For independent off-grid REM systems, one of the most concerned issues is energy-supply security. Self-sufficiency of energy generation is directly reflected in the model. Solutions with a lower cost and a higher efficiency can be generated to achieve optimal allocations of energy activities/services among the three communities. As a result, cooperative and independent energy production modes within the three communities can be reflected. It is impractical for each community to independently produce electricity from renewable energy sources due to varied geographic, political and economic conditions. Comparatively, it is more realistic to produce electricity in a cooperative way to obtain most cost-effective supply patterns. As indicates in Table 5, hydropower would be primarily from the community 1 with [33.7, 33.8], [15.0, 15.0], and [30.0, 30.0] TJ under $p_i = 0.01$ over periods 1, 2 and 3, respectively ([30.3, 30.3], [18.5, 18.5] and [30.0, 30.0] TJ under $p_i = 0.05$; [13.8, 13.8], [35.0, 35.0] and [30.0, 30.0] TJ under $p_i = 0.1$). Electricity from solar energy would be produced in community 2 ([35.8, 40.5], [31.3, 36.1] and [26.8, 31.6] TJ under $p_i = 0.01$; [39.2, 44.0], [33.8, 38.6] and [29.4, 34.2] TJ under $p_i = 0.05$; [40.8, 45.6], [33.3, 38.1] and [28.3, 33.1] TJ under $p_i = 0.1$). Most of the wind energy utilization activities would be occurring in community 3 (0, [38.6, 38.6] and [35.3, 35.3] TJ under $p_i = 0.01$; 0, [32.6, 32.6] and [39.2, 39.2] TJ under $p_i = 0.05$; [14.9, 14.9], [16.6, 16.6] and [41.6, 41.6] TJ under $p_i = 0.1$). These variations are mainly due to dynamics of economic costs in the planning horizon.

5. Conclusions

An ICS-EM has been developed for planning REM systems under uncertainty. This method is based on an integration of the existing ILP, CCP and MILP techniques. It allows uncertainties presented as both probability distributions and interval values to be incorporated within a general optimization framework. Moreover, ICS-EM can facilitate capacity-expansion planning for energy-production facilities within a multi-period and multi-option context. It improves upon the existing approaches for REM systems planning, such that robustness of the optimization process is enhanced. The generated solutions can be used for examining various decision options that are associated with different levels of risks when availabilities of renewable energy resources are limited. Probabilistic distributions of wind- and solar-energy availabilities can be integrated into the optimization process through the introduction of chance-constrained program (CCP) under a series of p_i levels. A higher p_i level would lead to a higher probability of system-constraint violation and a lower system cost; a lower p_i level would represent a lower probability of system-constraint violation under demanding conditions for resource availabilities, and thus a higher system cost. The interval solution under different p_i levels can be used for generating multiple decision alternatives, which would be useful for analyzing tradeoffs between economic and energy-security objectives.

The developed method has then been applied to a case of long-term renewable energy management planning for three communities. Violations of resource availabilities are allowed under a range of significance levels. Interval solutions associated with different risk levels of constraint violation have been obtained. They can be used for generating decision alternatives and thus help decision makers identify desired policies under various economic and system-reliability constraints. The generated solutions can provide desired energy resource/service allocation and capacity-expansion plans with a minimized system cost, a maximized system reliability and a maximized energy security. Tradeoffs between system costs and constraint-violation risks can also be tackled. Higher costs will increase system stability, while a desire for lower system costs will run into a risk of potential instability of the management system. The obtained solutions can also be used for examining the relations between increased certainties (or decreased resource availabilities) and decreased securities (or increased system-violation risks).

Acknowledgements

This research was supported by the Major State Basic Research Development Program of MOST (2005CB724200 and 2006CB403307) and the Natural Science and Engineering Research Council of Canada.

References

[1] Albrecht J. The future role of photovoltaics: a learning curve versus portfolio perspective. Energy Policy 2007;35(4):2296–304.
[2] Kazmerski LL. Photovoltaics: a review of cell and module technologies. Renew Sustain Energy Rev 1997;1(1/2):71–170.
[3] Marechal F, Favrat D, Jochem E. Energy in the perspective of the sustainable development: the 2000W society challenge. Resour Conserv Recycl 2005;44(3):245–62.
[4] Asif M, Muneer T. Energy supply, its demand and security issues for developed and emerging economies. Renew Sustain Energy Rev 2007;11(7):1388–413.
[5] Cai YP, Huang GH, Nie XH, Li YP, Tan Q. Municipal solid waste management under uncertainty: a mixed interval parameter fuzzy-stochastic robust programming approach. Environ Eng Sci 2007;24(3):338–52.
[6] Nfah EM, Ngundam JM, Tchinda R. Modeling of solar/diesel/battery hybrid power systems for far-north Cameroon. Renew Energy 2007;32(5):832–44.
[7] Zoulias EI, Lymberopoulas N. Techno-economic analysis of the integration of hydrogen energy technologies in renewable energy-based stand-along power system. Renew Energy 2007;32(4):680–96.
[8] Dutton AG, Bleijs JAM, Dienhart H, Falchetta M, Hug W, Prischich D, et al. Experience in the design, sizing, economics, and implementation of autonomous wind-powered hydrogen production systems. Int J Hydrogen Energy 2000;25(8):697–793.

[9] Huang GH, Baetz BW, Patry GG. Capacity planning for municipal solid waste management systems under uncertainty—a grey fuzzy dynamic programming (GFDP) approach. J Urban Plan Dev 1994; 120:132–56.
[10] Yeomans JS, Huang GH, Yoogalingam R. Combining simulation with evolutionary algorithms for optimal planning under uncertainty: an application to municipal solid waste management planning in the regional municipality of Hamilton-Wentworth. J Environ Inform 2003;2(1):11–30.
[11] World Energy Council (WEC). Comité Espanŏl del Consejo Mundial de la Energia, EDF, UNESCO. Energy Dictionary. Jouve Systemes d'Information; 1992; Bessanova TW, Kulenov NS. Econometric models for energy consumption. Colloquium Alma Ata: United Nations; 1973.
[12] World Energy Council (WEC). Energy for tomorrow's world. London: World Energy Council, St. Martins Press; 1993.
[13] Katscher W. IKARUS-Instruments for greenhouse gas reduction strategies. Interim Summary Report, KFA Julich; 1993.
[14] IER. Emission reduction of energy-related and climate-relevant trace gases in the Federal Republic of Germany and in Baden-Wuerttemberg. Stuttgart, Germany: University of Stuttgart; 1995.
[15] Wene CO. Energy-economy analysis: linking the macroeconomic and system engineering approaches. Energy 1996;21(9):809–24.
[16] Fujii Y, Yamaji K. Assessment of technological options in the global energy system for limiting the atmospheric CO_2 concentration. Environ Econ Policy Stud 1998;1:113–39.
[17] Howells MI, Alfstad T, Victor DG, Goldstein G, Remme U. A model of household energy services in a low-income rural African village. Energy Policy 2005;33(14):1833–51.
[18] Berglund C, Sőderholm P. Modeling technical change in energy system analysis: analyzing the introduction of learning-by-doing in bottom-up energy models. Energy Policy 2006;34(12):1344–56.
[19] Endo E, Ichinohe M. Analysis on market deployment of photovoltaics in Japan by using energy system model MARKAL. Sol Energy Mater Sol Cell 2006;90(18/19):3061–7.
[20] Turtona H, Barreto L. Long-term security of energy supply and climate change. Energy Policy 2006;34(5):2232–50.
[21] Blesl M, Das A, Fahl U, Remme U. Role of energy efficiency standards in reducing CO_2 emissions in Germany: an assessment with TIMES. Energy Policy 2007;35(2):772–85.
[22] Wang X. Environmental informatics for environmental planning and management. J Environ Inform 2007;9(1):1–3.
[23] Birge JR, Louveaux FV. A multicut algorithm for two-stage stochastic linear programs. Eur J Oper Res 1988;34:384–92.
[24] Cormio C, Dicorato M, Minoia A, Trovato M. A regional energy planning methodology including renewable energy sources and environmental constraints. Renew Sustain Energy Rev 2003;7(2):99–130.
[25] Yang XH, Yang ZF, Shen ZY. GHHAGA for environmental systems optimization. J Environ Inform 2005;5(1):36–41.
[26] Dantzig GB. Linear programming and extensions, revised edition, Princeton, NJ: Princeton University Press; 1966.
[27] Delson JK, Shahidehpour SM. Linear programming applications to power system economics, planning and operations. IEEE Trans Power Syst 1992;7(3):15–28.
[28] Yao JT, Liu WN, Fan L, Yao YY, Yang XD. Supporting sustainable communities with web-based information systems. J Environ Inform 2006;7(2):84–94.
[29] Hiremath RB, Shikha S, Ravindranah NH. Decentralized energy planning: modeling and application—a review. Renew Sustain Energy Rev 2007;11(5):729–52.
[30] Zeng Y, Trauth KM. Internet-based fuzzy multicriteria decision support system for planning integrated solid waste management. J Environ Inform 2005;6(1):1–15.
[31] Rehman S, El-Amin IM, Ahmad F, Shaahid SM, Al-Shehri AM, Bakhashwain JM, et al. Feasibility study of hybrid retrofits to an isolated off-grid diesel power plant. Renew Sustain Energy Rev 2007;11(4): 635–53.
[32] Wene CO, Rydén B. A comprehensive energy model in the municipal energy planning process. Eur J Oper Res 1988;33(2):212–22.
[33] Tessmer RG, Hoffman KC, Marcuse W, Behling DJ. Coupled energy system-economic models and strategic planning. Comput Oper Res 1975;2:213–24.
[34] Fishbone LG, Abilock HM. MARKAL, a linear programming model for energy systems analysis: technical description of the BNL version. Int J Energy Res 1981;5:353–75.
[35] Unger T, Ekvall T. Benefits from increased cooperation and energy trade under CO_2 commitments—the Nordic case. Climate Policy 2003; 3(3):279–94.
[36] Henning D, Amiri S, Holmgren K. Modelling and optimisation of electricity, steam and district heating production for a local Swedish utility. Eur J Oper Res 2006;175(2):1224–47.
[37] Stock KJ, Musgrove AR. MENSA: a regionalized version of MARKAL. Australia: The International Energy Association; 1984.
[38] Finon D. Un modele energetique pour la France. Paris: Centre Nationale de la Recherche Scientifique; 1976.
[39] Van der Voort E. Interest rate and output price uncertainty and industry equilibrium for non-renewable resource extracting firms. Resour Energy 1985;10:1–14.
[40] Khella AFA. Egypt: energy planning policies with environmental considerations. Energy Policy 1997;25(1):105–15.
[41] Grohnheit PE, Mortensen BOG. Competition in the market for space heating: district heating as the infrastructure for competition among fuels and technologies. Energy Policy 2003;31(9):817–26.
[42] Chinese D, Meneghetti A, Nardin G. Waste-to-energy based greenhouse heating: exploring viability conditions through optimization models. Renew Energy 2005;30(10):1573–86.
[43] Backus G, Amlin J, Kleeman S. Introduction to energy 2020. Fairborn, OH, USA: Systematic Solutions, Inc.; 1993.
[44] SEI (Stockholm Environment Institute). LEAP, Long range energy alternatives planning system, user guide. Boston, MA, USA: SEI, Tellus Institute; 1995.
[45] EIA (Energy Information Administration, U.S. Department of Energy), 1996. The national energy modeling system: an overview. DOE/EIA-0581(96), Washington, DC, USA.
[46] Islam SMN. Sustainable economic developments in the Australian energy sector: findings of the Australian energy planning system optimization model (AEPSOM). Renew Sustain Energy Rev 1997; 1(3):229–36.
[47] Huang LM, Hauqe E, Barg S. Public policy discourse, planning and measures toward sustainable energy strategies in Canada. Renew Sustain Energy Rev 2008;12(1):91–115.
[48] Khan FI, Hqwboldt K, Iqbal MT. Life cycle analysis of wind–fuel cell integrated system. Renew Energy 2005;30(2):157–77.
[49] Ashok S. Optimized model for community-based hybrid energy system. Renew Energy 2007;32(7):1155–64.
[50] El-Shatter TF, Eskander MN, El-Hagry MT. Energy flow and management of a hybrid wind/PV/fuel cell generation system. Energy Convers Manage 2006;47(9/10):1264–80.
[51] Polatidis H, Haralambopoulos DA. Renewable energy systems: a societal and technological platform. Renew Energy 2007;32(2): 329–41.
[52] Iniyan S, Sumathy K. An optimal renewable energy model for various end-uses. Energy 2000;25:563–75.
[53] Huang GH, Batez BW, Patry GG. A grey linear programming approach for municipal solid waste management planning under uncertainty. Civil Eng Environ Syst 1992;9:319–35.
[54] Huang GH, Baetz BW, Patry GG. Grey quadratic programming and its application to municipal solid waste management planning under uncertainty. Eng Optim 1995;23:201–23.
[55] Huang GH, Baetz BW, Patry GG. Grey integer programming: an application to waste management planning under uncertainty. Eur J Oper Res 1995;83:594–620.
[56] Huang GH. A hybrid inexact-stochastic water management model. Eur J Oper Res 1998;107(1):137–58.
[57] Cai YP, Huang GH, Yang ZF, Lin QG, Bass B, Tan Q. Development of an optimization model for energy systems planning in the Region of Waterloo. Int J Energy Res 2007. doi: 10.1002/er.1407.

[58] Huang GH, Chang NB. The perspectives of environmental informatics and systems analysis. J Environ Inform 2003;1(1):1–7.
[59] Liu L, Huang GH, Liu Y, Fuller GA. A fuzzy-stochastic robust programming model for regional air quality management under uncertainty. Eng Optim 2003;35(2):177–99.
[60] Luo B, Yin YY, Huang GH, Huang YF. Uncertainty analysis for distribution of greenhouse gases concentration in atmosphere. J Environ Inform 2004;3(2):89–94.
[61] Nie XH, Huang GH, Li YP, Liu L. IFRP: a hybrid interval-parameter fuzzy robust programming approach for waste management planning under uncertainty. J Environ Manage 2007;84(1):1–11.
[62] Akisawa A, Kang YT, Shimazaki Y, Kashiwagi T. Environmentally friendly energy system models using material circulation and energy cascade—the optimization work. Energy 1999;24(7):561–78.
[63] Khan MJ, Iqbal MT. Pre-feasibility study of stand-alone hybrid energy systems for applications in Newfoundland. Renew Energy 2005; 30(6):835–54.
[64] Gan ZJ, Elganovan S, Khincha HP, Li Z. Design of a complete multi-microcontroller based protection system for large diesel turbine generator. Electr Power Syst Res 1997;40(2):99–105.
[65] Ghosh PC, Emonts B, Stolten D. Comparison of hydrogen storage with diesel-generator system in a PV–WEC hybrid system. Sol Energy 2003;75(3):187–98.
[66] Zahedi A, Smieee. Development of an electrical model for a PV/battery system for performance prediction. Renew Energy 1998;15(1–4): 531–4.
[67] de Vries BJM, van Vuuren DP, Hoogwijk MM. Renewable energy sources: their global potential for the first-half of the 21st century at a global level: an integrated approach. Energy Policy 2007;35(4):2590–610.
[68] Cassidy P, Scott L. Minimising costs of wind: risk control and operation and maintenance strategies. Refocus 2002;3(5):34–7.
[69] Söderholm P, Ek K, Pettersson M. Wind power development in Sweden: global policies and local obstacles. Renew Sustain Energy Rev 2007; 11(3):365–400.